Energy+Environmental Economics

Machine Learning for Net Load Uncertainty

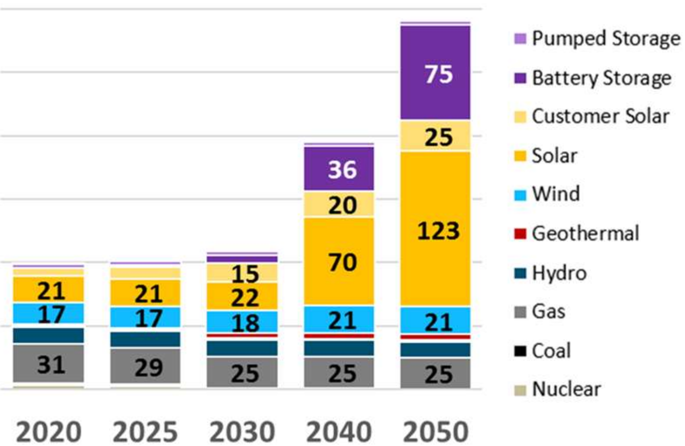
2020 INFORMS Conference

Arne Olson

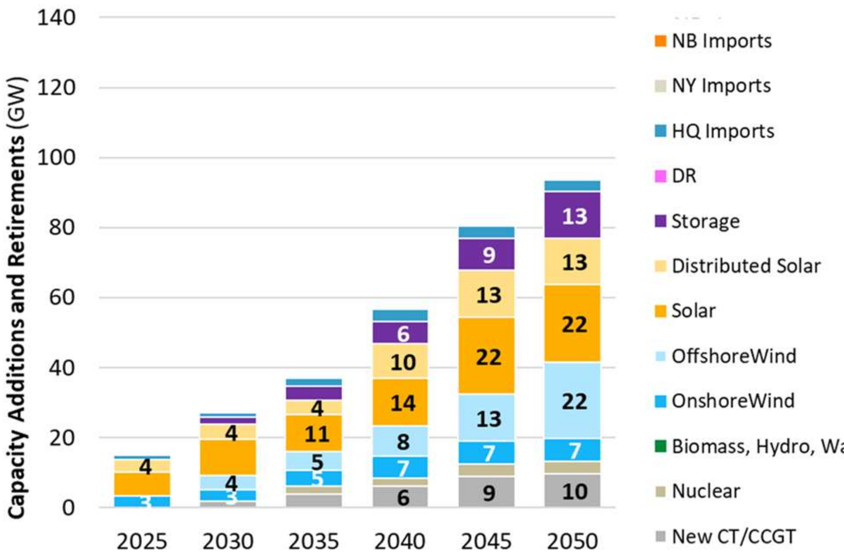
Senior Partner

Wind and solar central to economy-wide decarbonization

2050 Portfolio Achieving 92% CO_2 reductions in California



2050 Portfolio Achieving 94% CO_2 reductions in New England



+ **Funding: ARPA-E Perform**

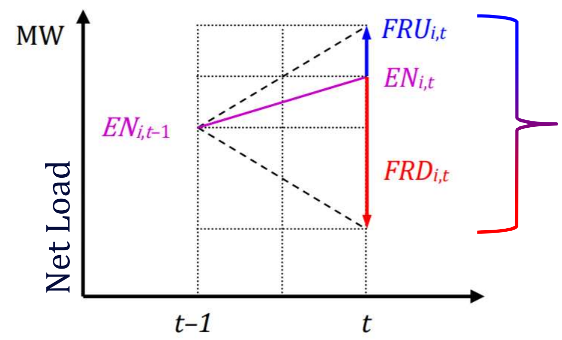
+ **Partnership**

Wind and solar amplify "fuel uncertainty"

- Grid operators have <u>always</u> balanced variability and uncertainty in demand and supply
- Wind and solar generators increase the magnitude of supply-side variability
  - Potential negative impacts to reliability if not properly managed
- "Net Load" is frequently used to quantify balancing requirements
  - Net load = Load – Wind Generation – Solar Generation

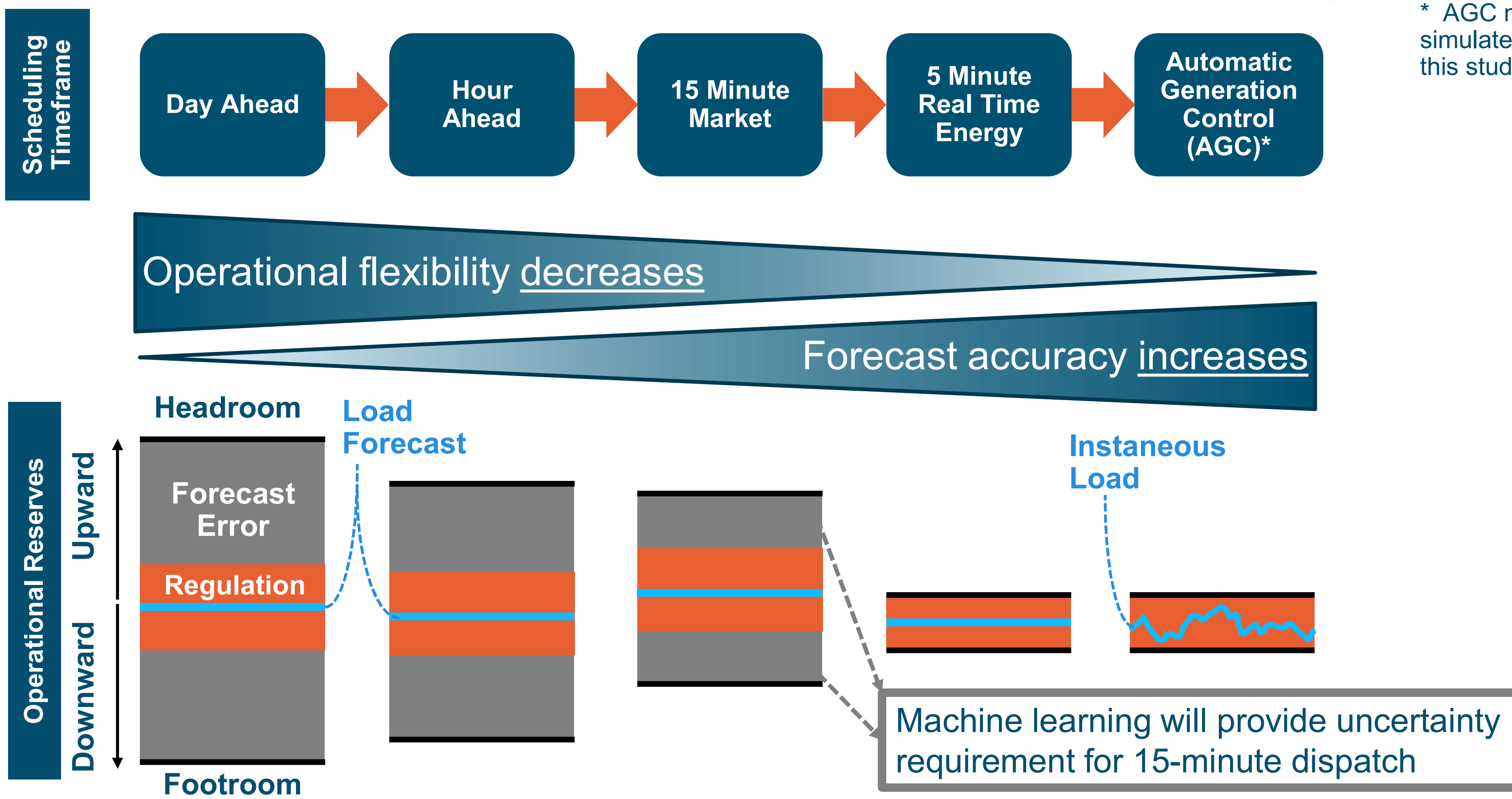
How big is the challenge?

- In 2019 CAISO ancillary service procurement cost was ~$150M. Wholesale market ~$8 Billion. E3 is targeting reducing total CAISO system production costs by 1-3% **(~$100M)** and GHG emissions by **~1.5 MMT CO_2/yr**
  - *Billions of dollars worldwide*
- In a highly renewable future CAISO grid, solar curtailment could be reduced by **15%** when at least 15% of CAISO FRP is procured from VERs



How far could net load *reasonably* be expected to go up or down between time intervals?

Scheduling timeframes and reserve needs



* AGC not simulated in this study

Root-Mean-Square -> Machine Learning

Our ARPA-E project focuses on reserves for forecast uncertainty of load, wind, and solar – a <u>non-event</u> type of reserve

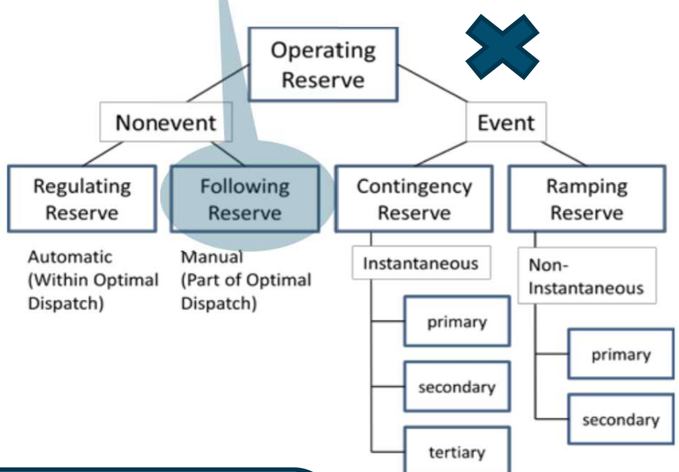
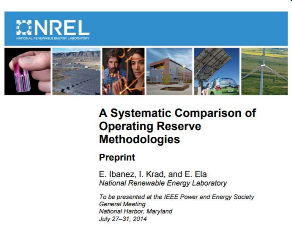
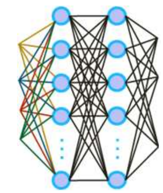
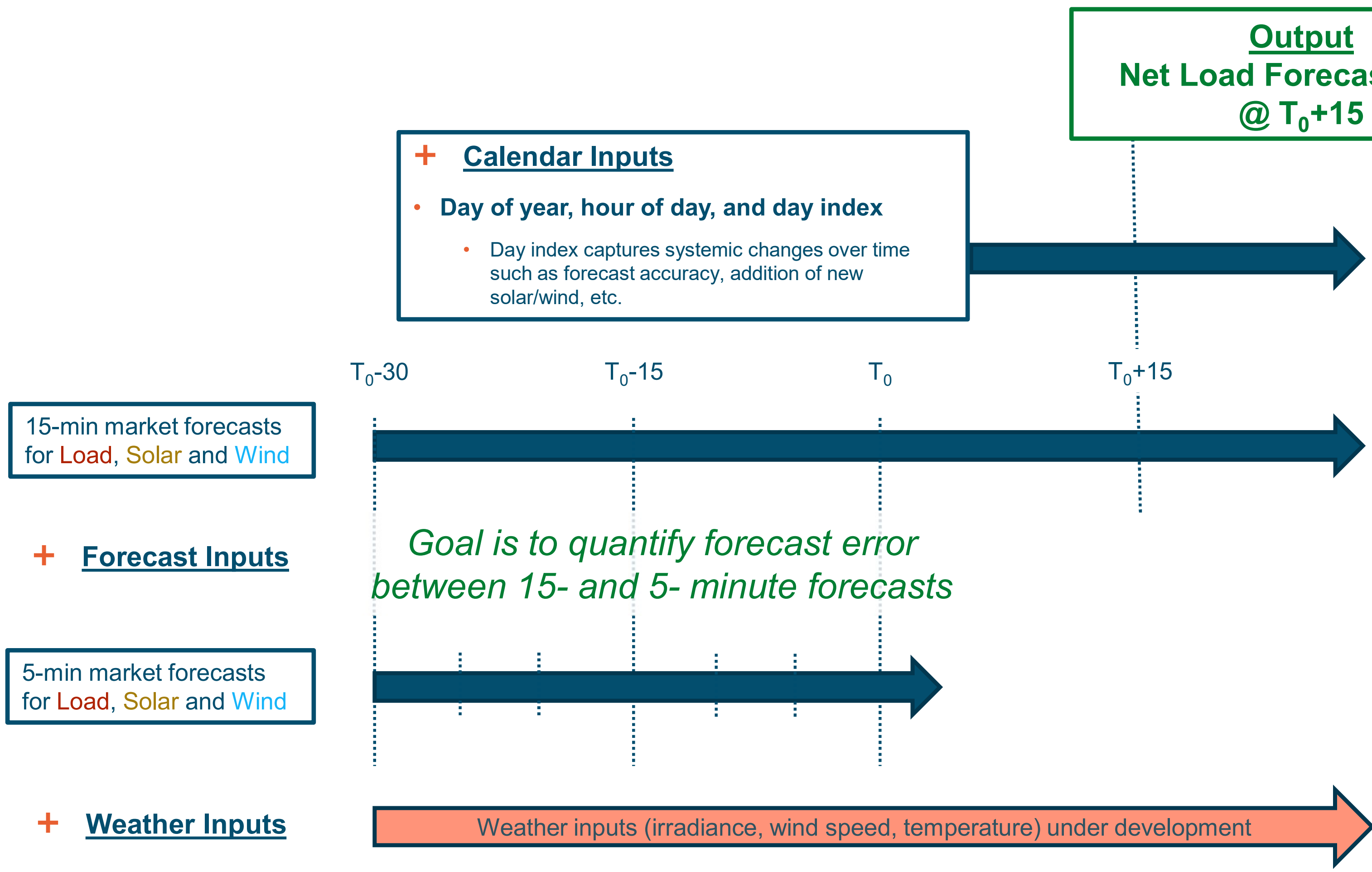


Fig. Source



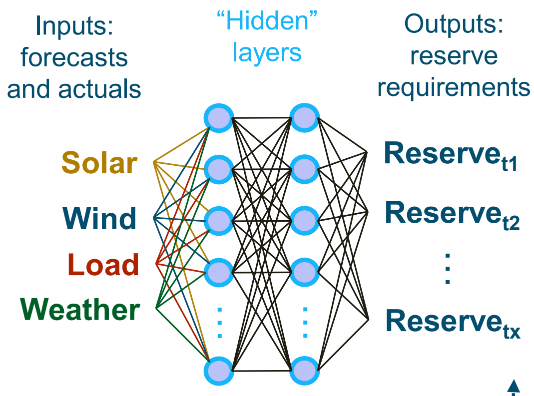
Root-mean-square (RMS) method is frequently used		Machine learning could offer significant advantages
$$\textit{Flexibility Reserve} = \sqrt{\Phi 70_{\text{hour-load}}{}^2 + \Phi 70_{\text{hour-wind}}{}^2 + \Phi 70_{\text{hour-PV}}{}^2}$$		
Assumes that error between L-W-S components is uncorrelated	**Correlations**	Can include underlying correlations resulting from coincident weather
Historical record has very sparse data to create a prediction interval at P95+	**Data**	Machine learning can "fill in" the data record by including drivers of under/overforecast events

Predicting Net Load Forecast Error



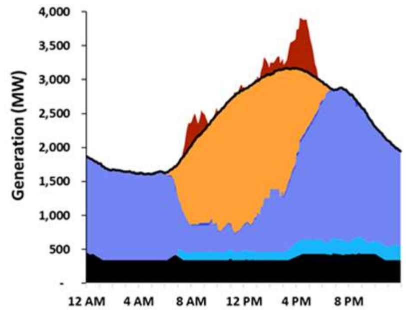
Study process

Machine learning generates reserve needs using artificial neural network



Adjust machine learning if system is not operable

PLEXOS production simulation of CAISO system validates operability



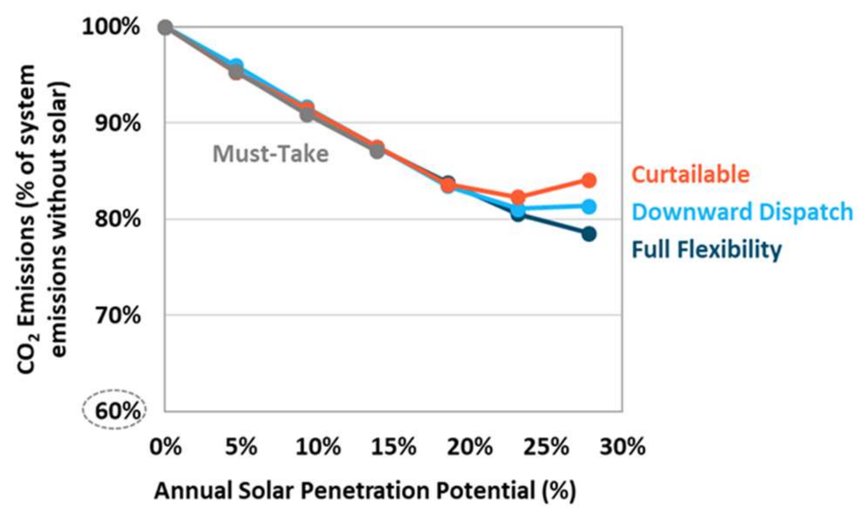
Summary and CAISO Comparison

- Quantify optimal level of reserve to hold
- Estimate cost and GHG savings
- Compare machine learning reserves to CAISO current practice

Wind and Solar Flexibility

- **Predicting *net* load implies that solar and wind won't be curtailed**
  - Net load = Load – [uncontrollable] Wind - [uncontrollable] Solar
- **A highly renewable grid will experience frequent curtailment**
  - Balancing requirements are overestimated during curtailment events
  - “Supply” of balancing resources can include controllable wind + solar
- **Machine learning will be used to develop balancing requirements when wind and solar are partially curtailed**
  - Also to develop limits on curtailed wind + solar contributing to flexibility/ramping needs

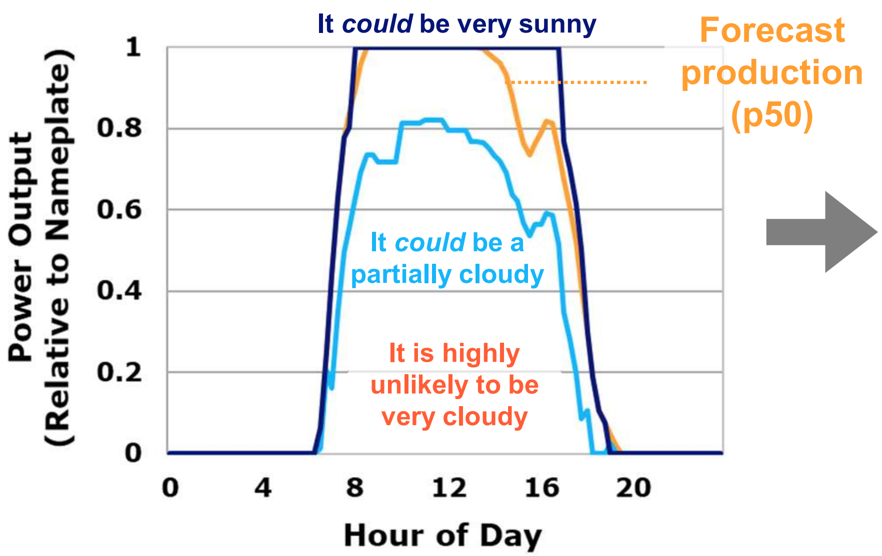
FirstSolar / TECO / E3 study on solar dispatch for Tampa Florida



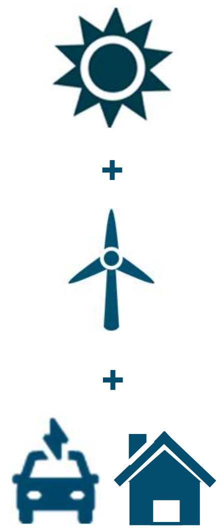
Operating and scheduling solar power plants in a more flexible manner results in lower CO_2 emissions

Machine learning provides renewable reserve limits

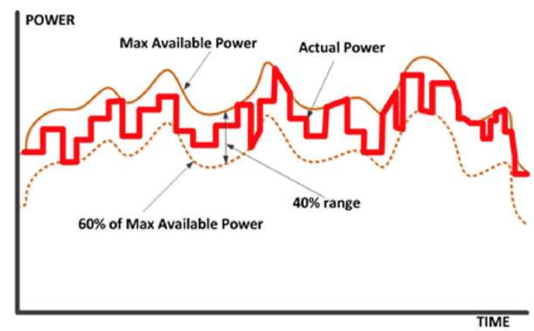
Input Data: Solar (or wind) forecast possibilities



Machine Learning estimates correlations between solar/wind and net load forecast error



Production simulation quantifies benefits of solar and wind reserves and ensures operability



Adjust machine learning or production simulation if system is not operable

Figure source: https://www.nrel.gov/docs/fy17osti/67799.pdf

Conclusions

- **E3 to work with the California Independent System Operator in formulating and evaluating E3's machine-learning module and PLEXOS model**
  - CAISO to provide system operator perspective on current practices
  - E3 to deliver tool to CAISO that allows for dynamic reserves predictions, CAISO to support E3 by evaluating this tool
  - E3 to release final version of this tool to CAISO and ARPA-E for their use at project conclusion
- **E3 would like to thank CAISO and ARPA-E for their support for this project**

- **Funding: ARPA-E Perform**

- **Partnership**

Project team

E3

Principal Investigator
Arne Olson

Project Managers
Jimmy Nelson

John Stevens

Machine Learning + Data Cleaning and Acquisition

Yuchi Sun

Charles Gulian

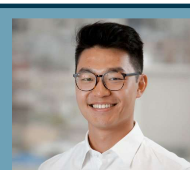
Vignesh Venugopal

Mengyao Yuan

PLEXOS

Saamrat Kasina

Adrian Au



California ISO

Project Manager
Clyde Loutan
Principal,
Renewable Energy Integration

Support
Peter Klauer
Senior Advisor, Smart Grid Technology

Guillermo Bautista Alderete
Director, Market Analysis and Forecasting

Energy+Environmental Economics

Thank You!

Energy and Environmental Economics, Inc. (E3)
44 Montgomery Street, Suite 1500
San Francisco, CA 94104
Tel 415-391-5100
Web http://www.ethree.com

Arne Olson, Senior Partner (arne@ethree.com)
Dr. Jimmy Nelson, Managing Consultant
Dr. John Stevens, Senior Consultant
Dr. Yuchi Sun, Consultant